

# Boosting Energy Efficiency of Heterogeneous Connected and Automated Vehicle (CAV) Fleets via Anticipative and Cooperative Vehicle Guidance



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Clemson University (CU)

International Transportation Innovation Center (ITIC)

Argonne National Laboratory (ANL)

2019 DOE VTO Annual Merit Review

June 13, 2019



Project ID  
EEMS029

## Timeline

- Project start date:
  - Sep. 1, 2017
- Project end date:
  - Aug. 31, 2019
- Percent complete: 75%

## Budget

- Total project funding
  - EERE: \$1,159,987
  - FFRDC: \$100,000
  - Cost share: \$183,206
  - Total: \$1,343,193
- Funding for Budget Period 1 (BP1):
  - \$ 542,099 (EERE)+\$50k (FFRDC)+109,853 (cost share)
- Funding for Budget Period 2 (BP2):
  - \$517,888(EERE)+\$50k (FFRDC)+\$79,373 (cost share)

## Barriers

- Evaluating the network-wide energy efficiency gains of connected and automated vehicles.
- Accurately modeling and simulating mixed-traffic conditions consisting of autonomous and human-controlled vehicles.
- Real-time integration of experimental vehicles into large- scale traffic micro-simulations for more accurate energy use measurement.

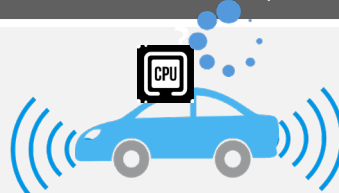
## Partners



## Connected and Automated Vehicles (CAVs)



By **Vehicle-to-vehicle (V2V) communication**, the event horizon of vehicles can be extended not only in time but also in space.



By **Autonomous Driving**, the incoming information can be processed effortlessly and the vehicle can be guided precisely.

Potential impact of CAVs in lowering energy use has received much less attention from the CAV research community.

### Overall Objectives

- Propose **anticipative and collaborative guidance schemes** for CAVs to lower energy use.
- Obtain energy impacts for a mixed traffic fleet using simulations and experiments.

### Objectives previous period (Go/No-Go decision point )

- up to 5% increase in energy efficiency for simulated CAVs using real-time implementable algorithms demonstrated in (Matlab) simulations.

### Objectives this period

- Demonstrating an additional 3%-5% increase in energy efficiency for simulated CAVs using our improved guidance algorithms (verifications using VISSIM microsimulations).

### Impact & Relevance to VT Office

- Potential of reducing abrupt maneuvers/slow downs and contributing to a **harmonized traffic flow**.
- Our findings could inform and shape new policies of VTO aimed at **accelerated deployment of CAVs to lower national energy consumption**.
- The VIL testing setup can find wider use across other VTO-funded initiatives.

# Our Approach

# Strategy

## Task 2 (simulation environment)

### Task 1 (algorithms)

Traffic  
Perception &  
Prediction

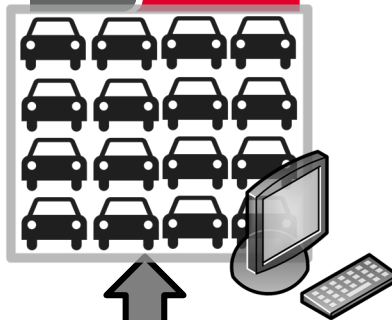
Anticipative  
Car  
Following

Anticipative  
Lane  
Selection



Real-time traffic microsimulation

PTV VISSIM



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Energy  
Analysis

Off-line simulation  
of high fidelity models



Wireless Communication Layer

## Task 3 (real world environment)

Real CAVs  
Instrumentation



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Testing

Test track



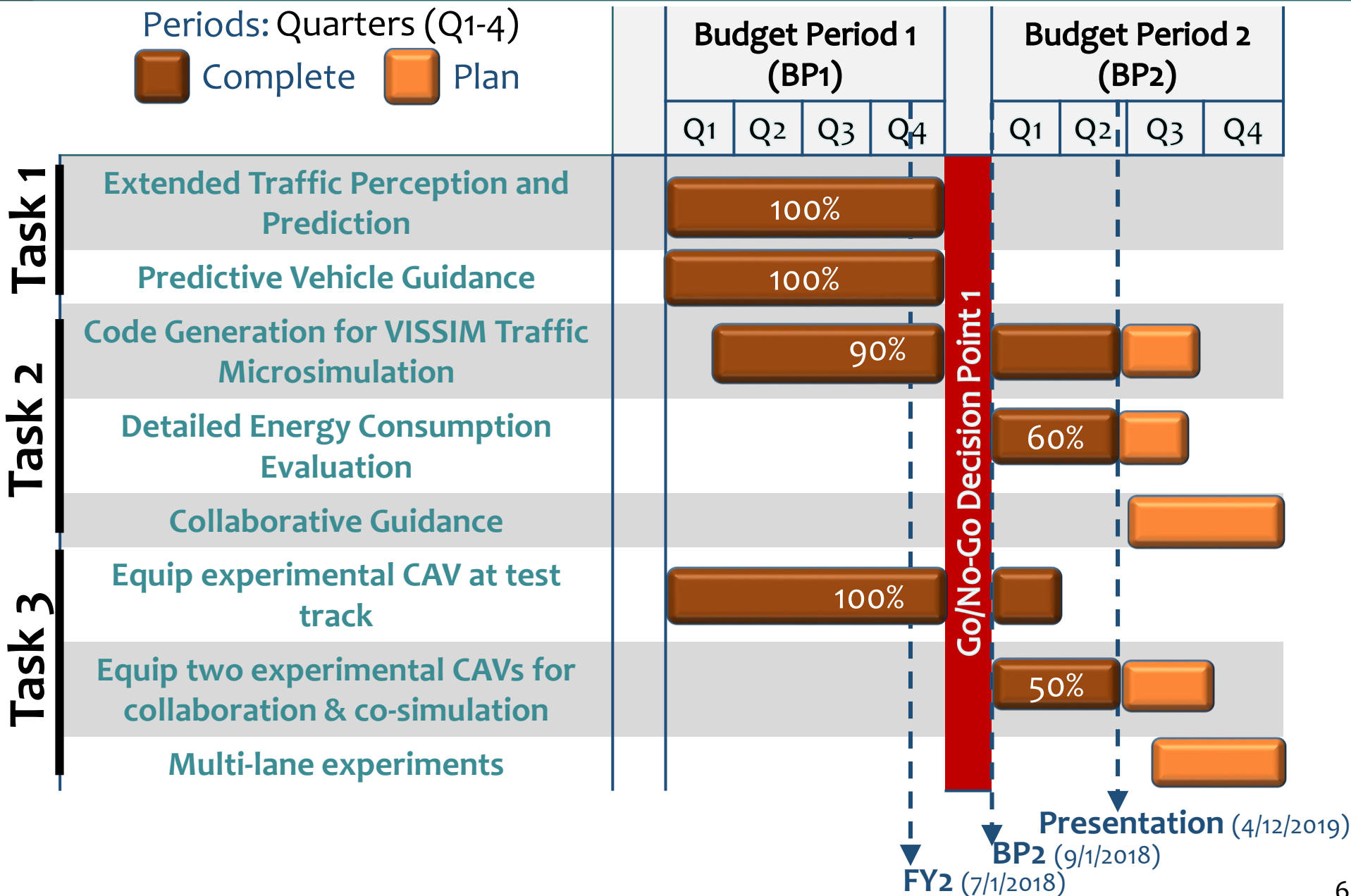
Energy  
Analysis

OBD Data  
Logger



CLEMSON  
UNIVERSITY

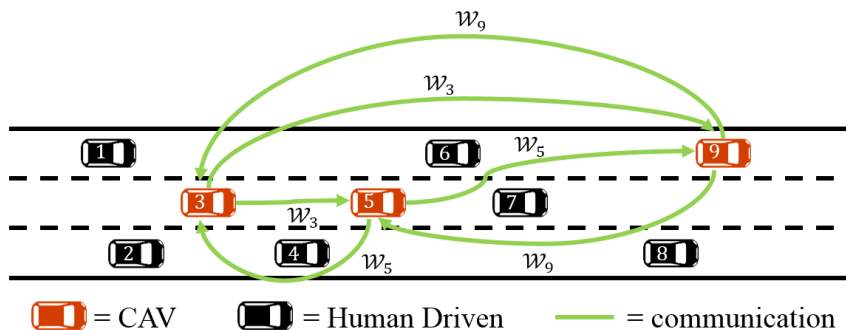
# Milestones & Progress Summary



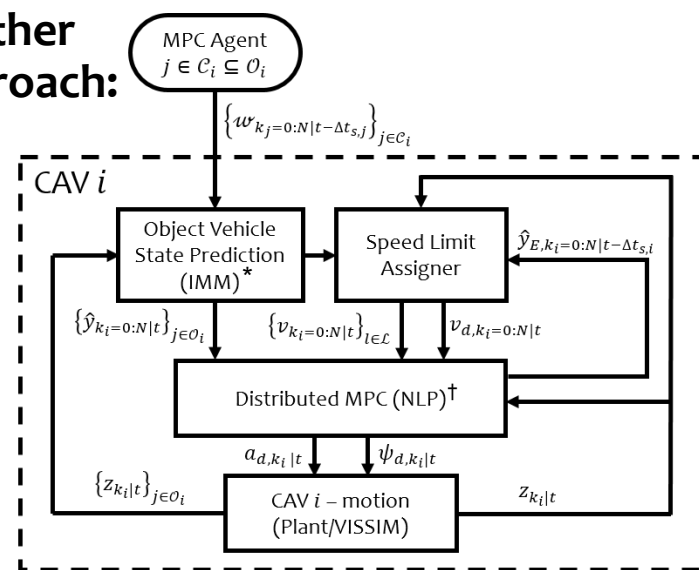
# Task 1 ➤ Anticipative Car-Following & Lane Selection

## ➤ Traffic Perception and Prediction

### Multi-Agent System:



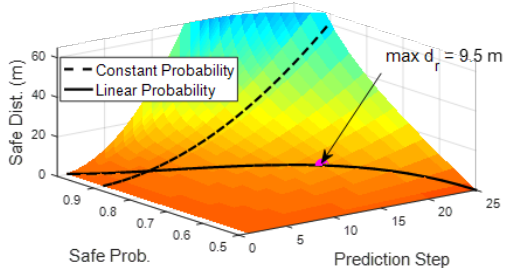
### Another Approach:



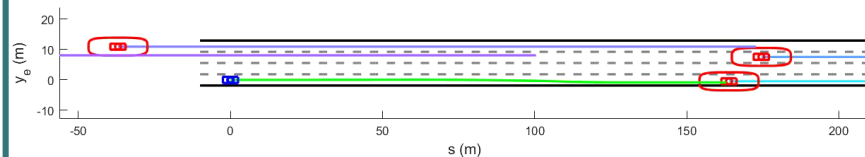
### One Approach:

#### Chance constraints for unconnected vehicles

**New**

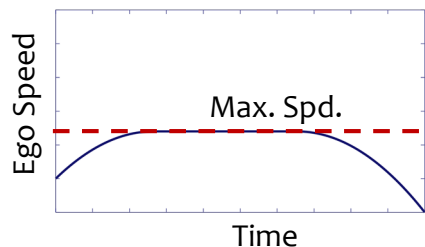


### Illustrative Scenario (Video):



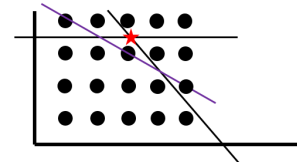
\*Interactive Multiple Model (IMM) Kalman Filter; †Non-Linear Program (NLP)

### Constrained Full-Trip Optimal Control



**New**

### MPC with Integer Lane Selection (MIQP)



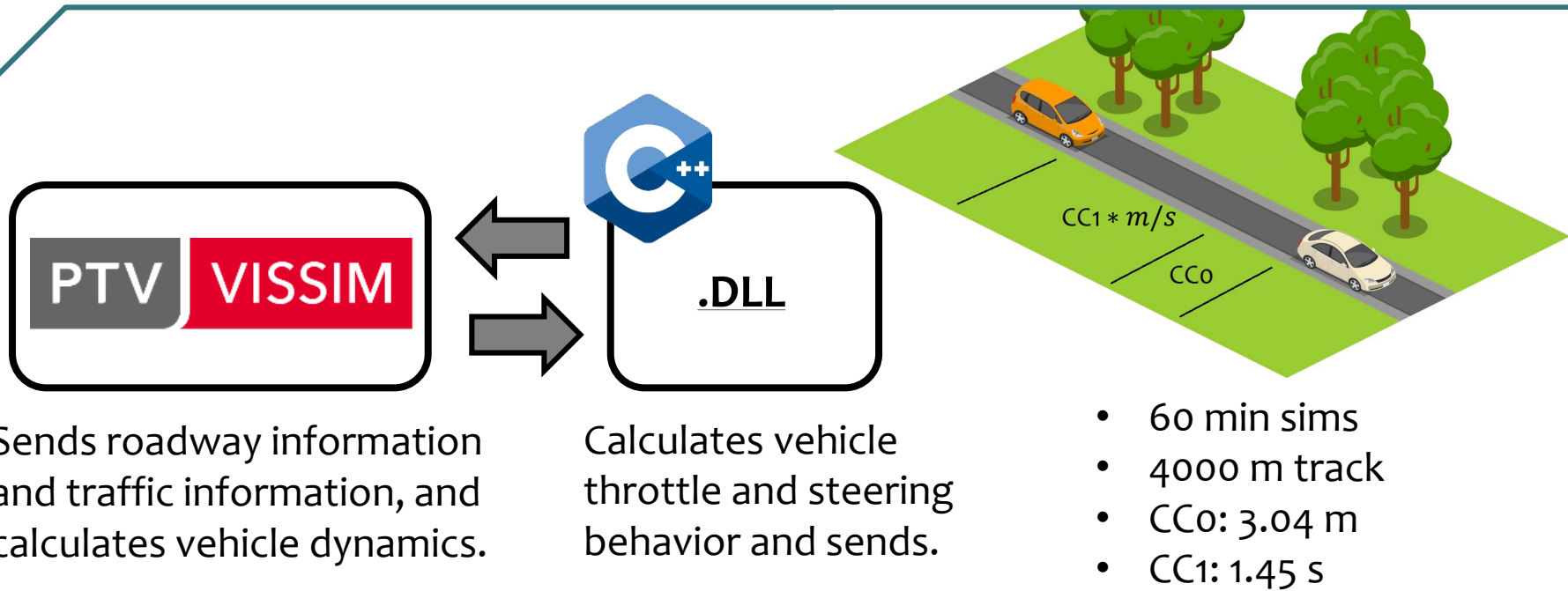
**Updated**

Accel. Cmd.

Lane Cmd.

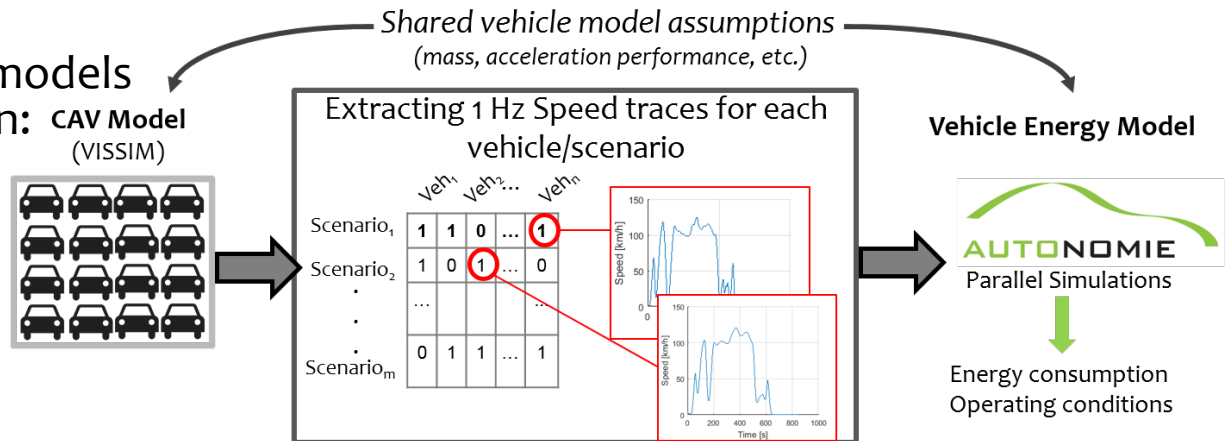
# Task 2 ➤ Simulation Model Creation for Mixed-Traffic

## ➤ Energy Consumption Models



[1] Dong, J., A. Houchin, N. Shafieirad, C. Lu, N. Hawkins, and S. Knickerbocker. 2015. *VISSIM Calibration for Urban Freeways*. Center for Transportation Research and Education, Institute for Transportation, Iowa State University, Ames

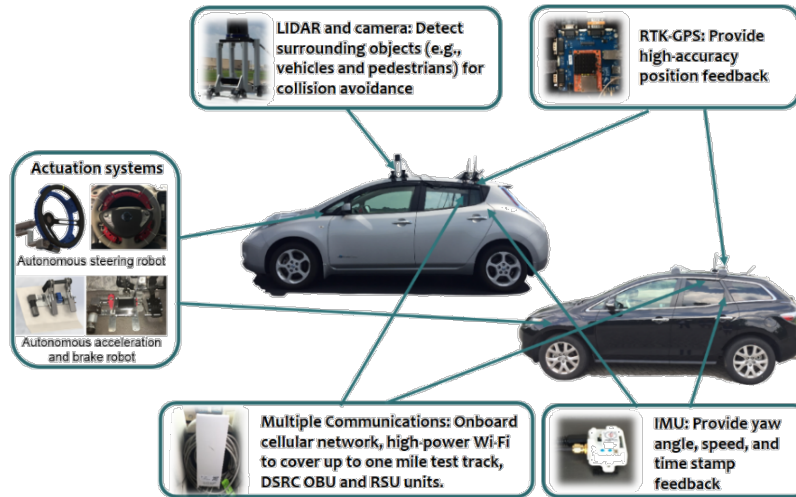
State-of-the-art Autonomie models used for energy consumption:



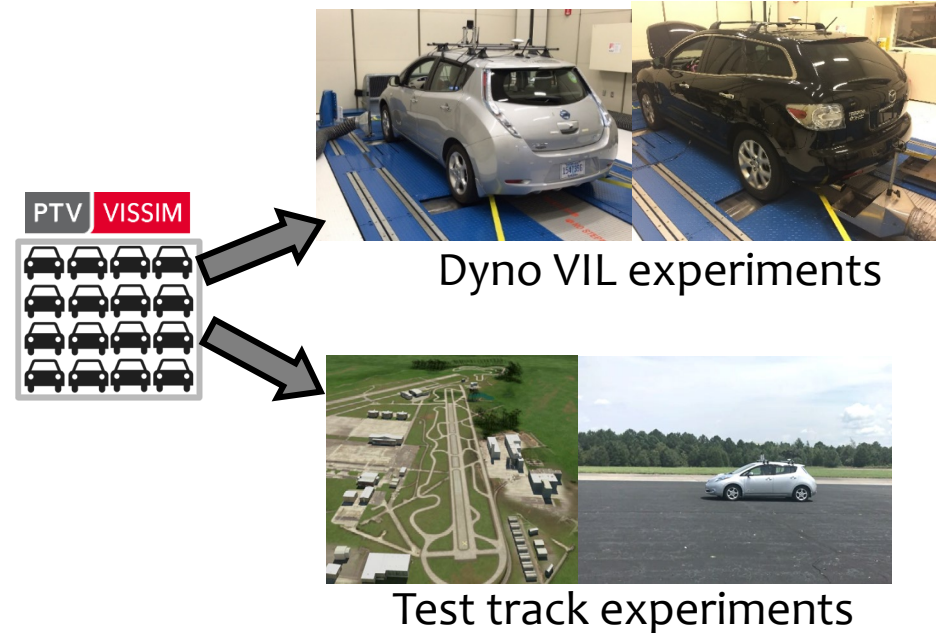
# Task 3 ➤ Vehicle-in-the-Loop Experimental Testbed ➤ Energy Consumption Evaluation

## CAV Instrumentation

(to turn Nissan Leaf and Mazda CX7 into autonomous-driving-capable vehicles )

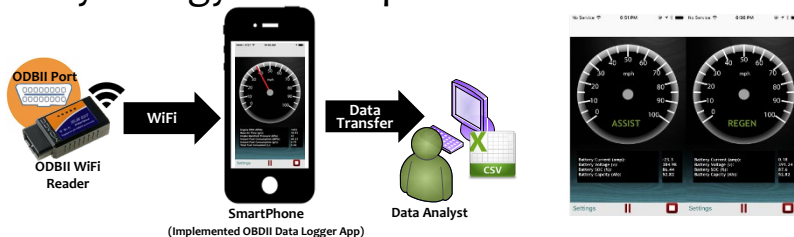


## Vehicle-in-the-Loop (VIL) Testbeds



## OBD-based Energy Estimation

A smartphone App is implemented to log data from the OBDII port and to estimate the fuel & battery energy consumption.



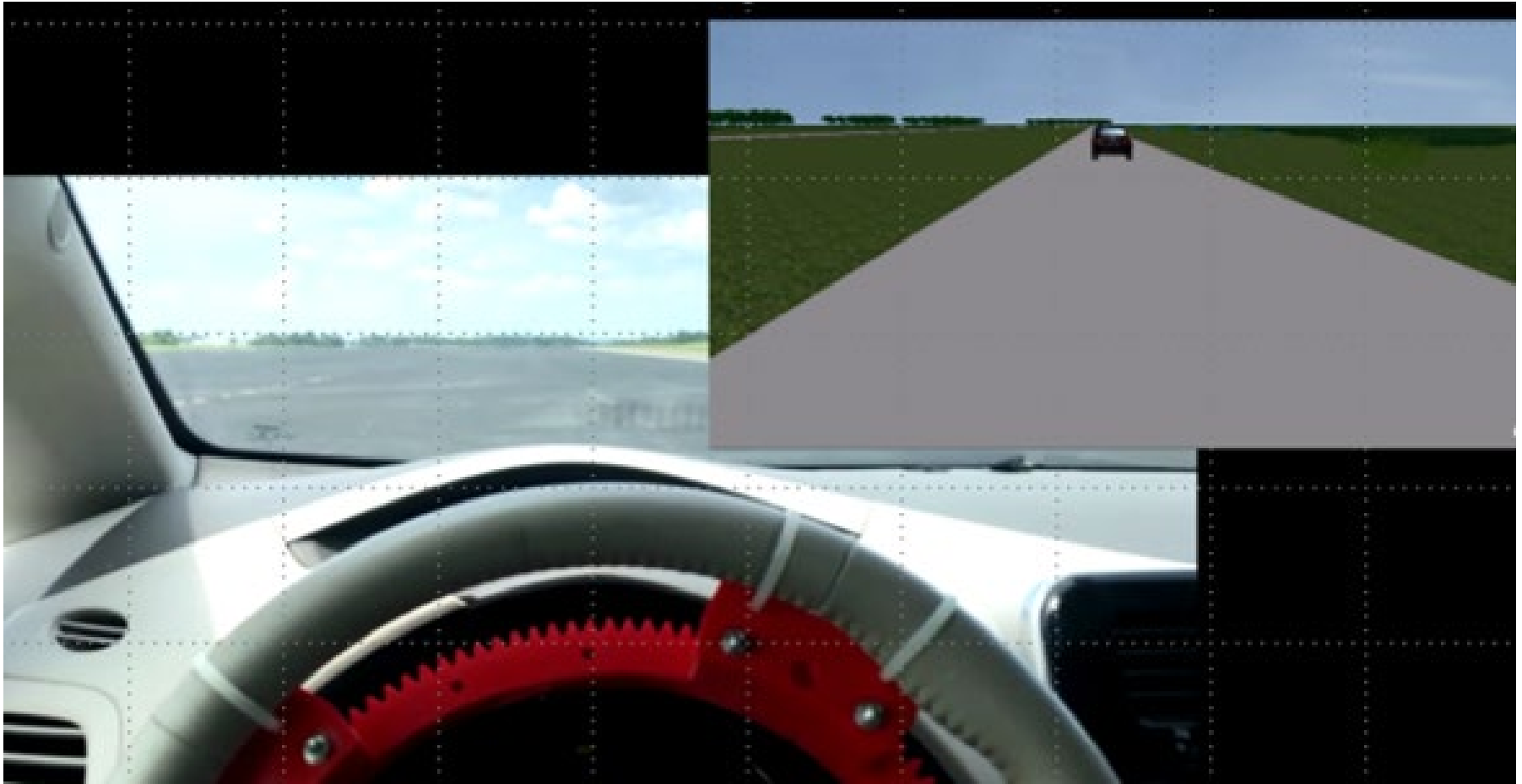
## Fuel Rate Measurement by Flow Meter

Flow meter is used to measure the fuel usage in a controlled environment and to evaluate our OBD-based fuel rate estimations.



# Task 3 ➤ Vehicle-in-the-Loop Experimental Testbed

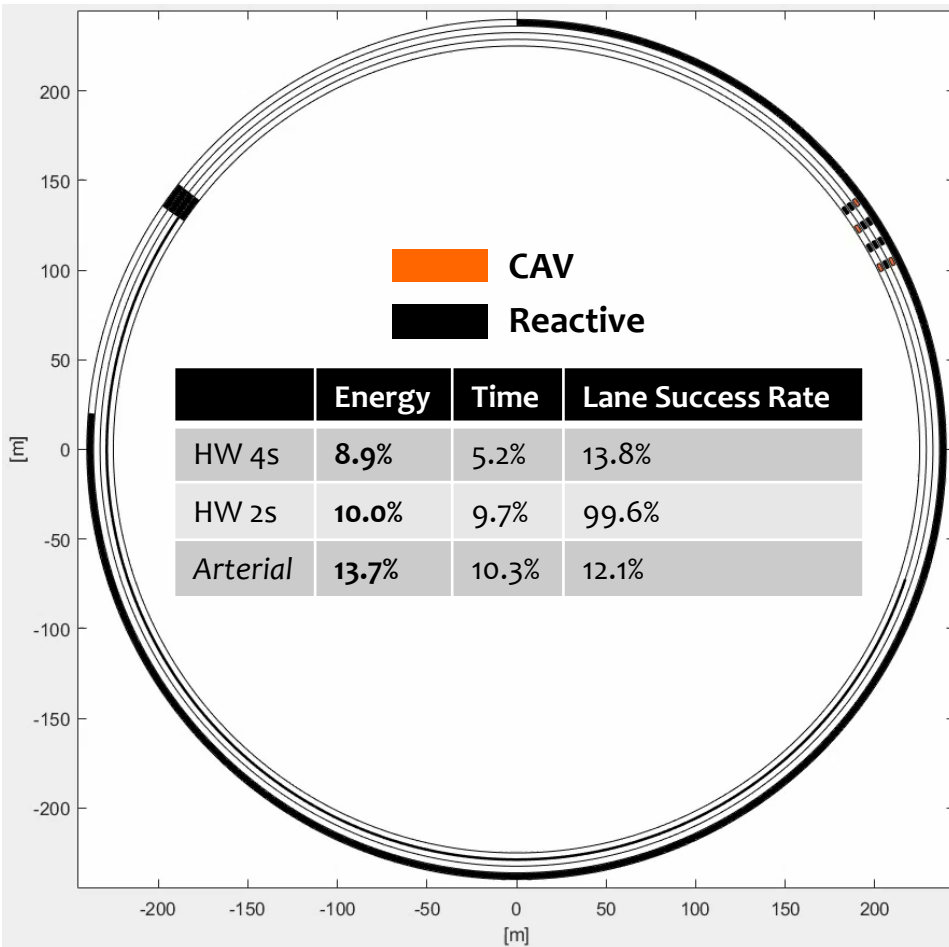
**VIL Testbed:** Real automated vehicle interacts with a virtual vehicle in VISSIM.



# Technical Accomplishments and Progress

# Accomplishments

## Anticipative CAVs Reduce Energy, Time vs. Reactive Model



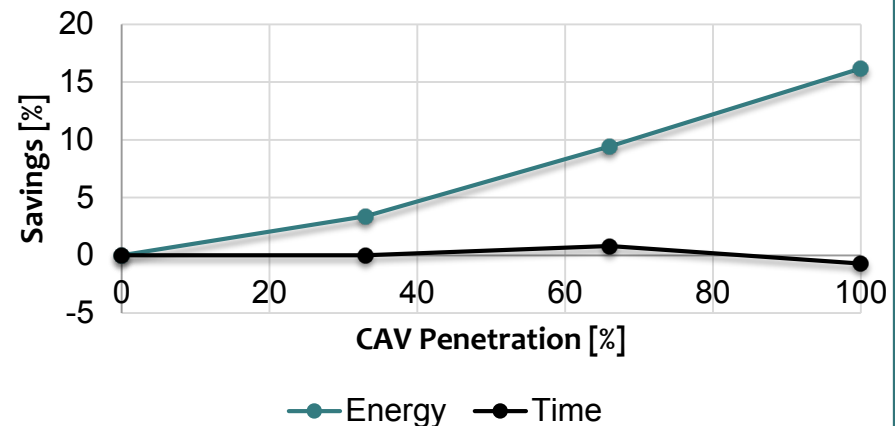
## Multi-Agent MATLAB Simulation Results

### Highway Merge Scenario

- Vehicles enter at either 0.5 Hz or 0.25 Hz.
- Random desired lane (highway or exit).



### Arterial, Time Matched to Baseline (video)



### Baseline: Intelligent Driver Model with Rule-Based lane change

- 2-lane version: R. A. Dollar and A. Vahidi, "Predictively coordinated vehicle acceleration and lane selection using mixed integer programming," in ASME 2018 Dynamic Syst. Control Conf., 2018, pp. 1–9.
- Multi-lane version: R. A. Dollar and A. Vahidi. "Automated vehicles in hazardous merging traffic: a chance-constrained approach." To appear, 2019 9<sup>th</sup> Int. Symp. Advances in Automotive Control, IFAC, 2019.

### Intelligent Driver Model for Car Following

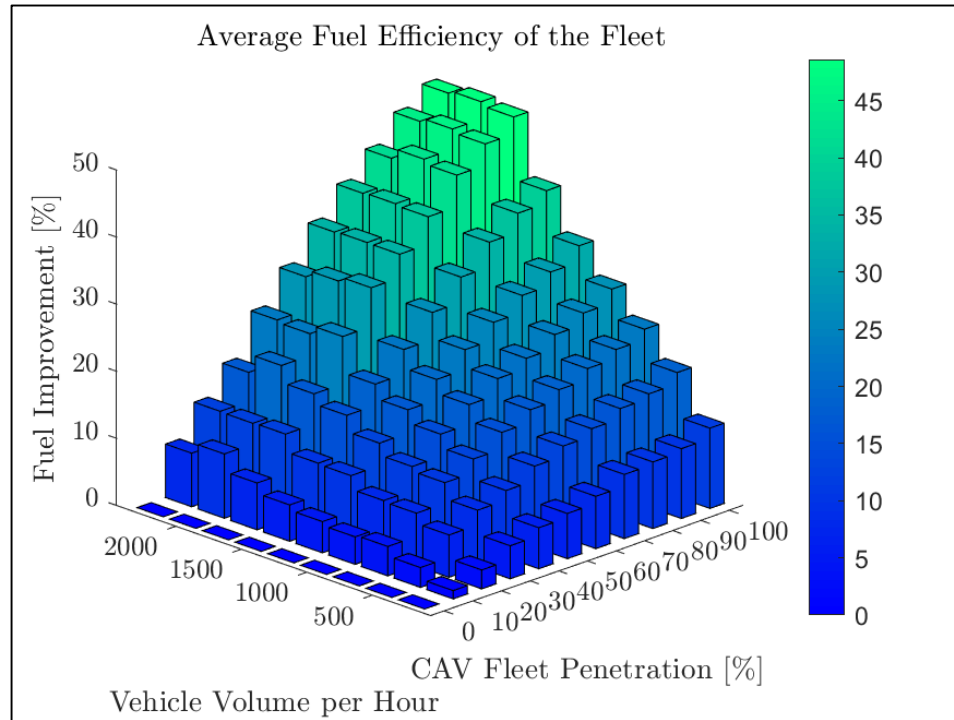
Treiber, M., Hennecke, A., and Helbing, D., 2000. "Congested traffic states in empirical observations and microscopic simulations". *Physical Review E*, 62(2), p. 1805.

$$d_{des} = d_0 + \max\left(0, \tau_h v + \frac{v \Delta v}{\sqrt{4a_0 b_0}}\right); u_1 = a_0 \left[1 - \left(\frac{v}{v_{ref}}\right)^{\delta_a} - \left(\frac{d_{des}(v, \Delta v)}{d}\right)^2\right]$$

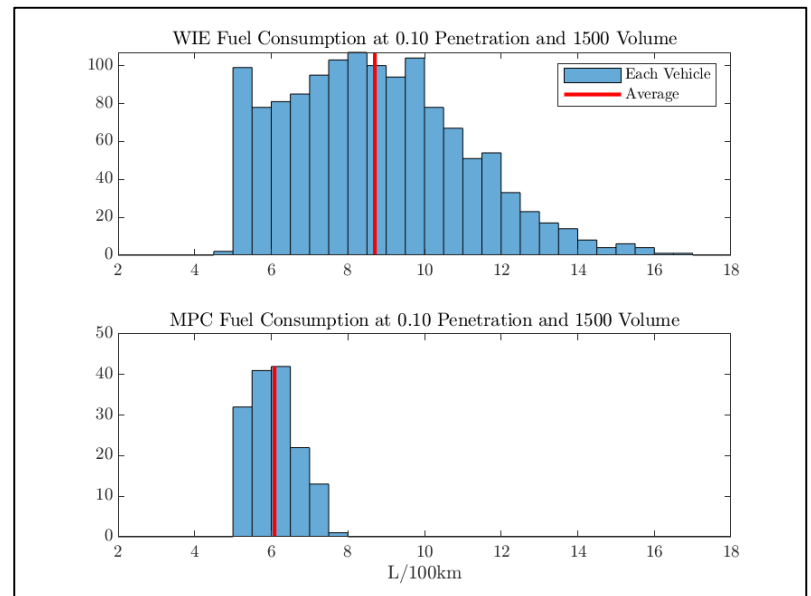
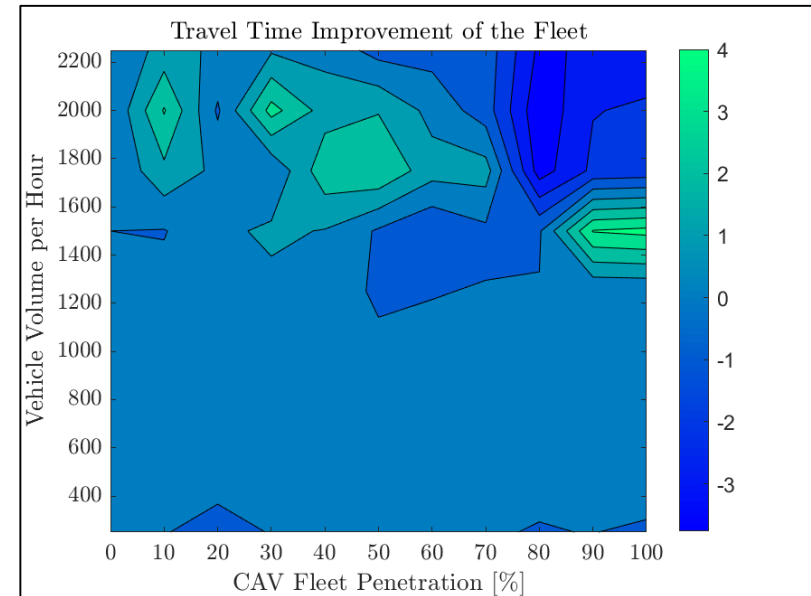
# Accomplishments

## Car-Following Microsimulation

- Matlab Results:



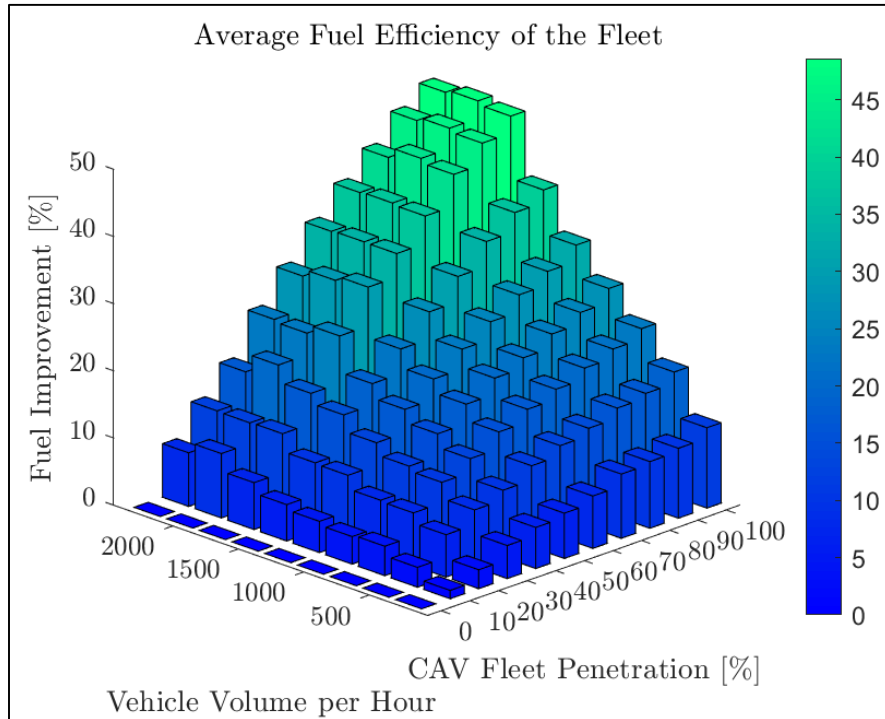
- Travel times were normalized to the Wiedemann drivers (WIE, Vissim model)
- At any penetration, it is expected MPC vehicles will have significantly lower fuel consumption



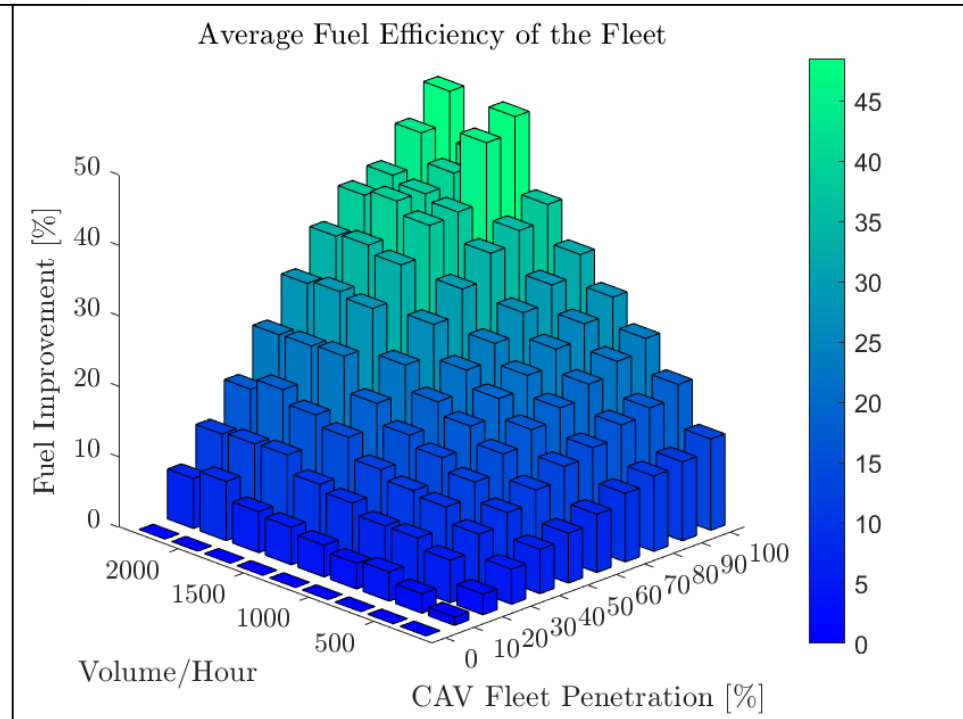
# Accomplishments

## Car-Following Microsimulation

- Matlab Results



- Autonomie Results

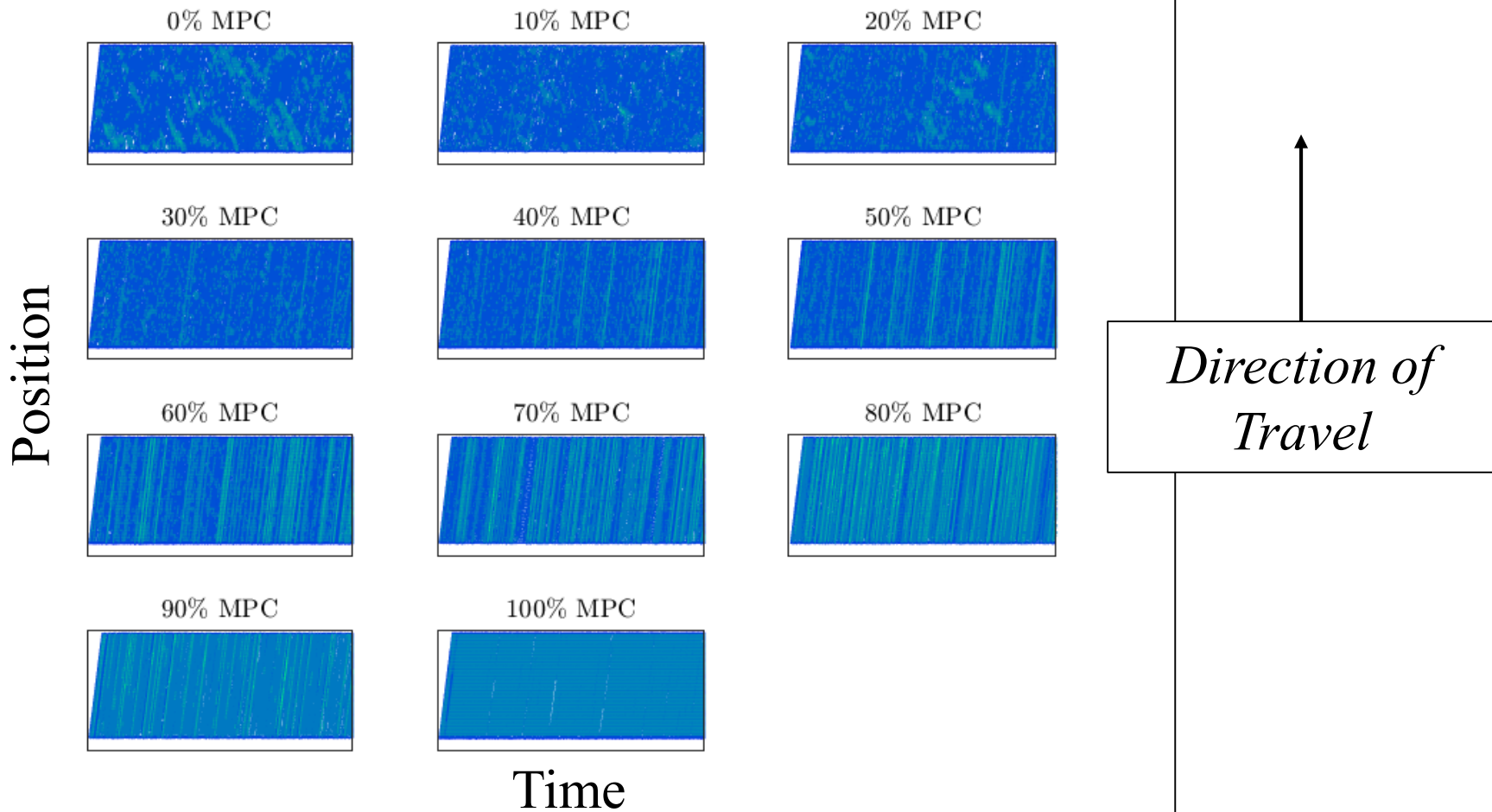


- High-fidelity processing in Autonomie shows similar results to Matlab model

# Accomplishments

## Car-Following Microsimulation

Cell Density in MPC Case at 2250 Volume



- Traffic smoothing effects are seen by a reduction in shockwaves and increasing density at higher penetrations

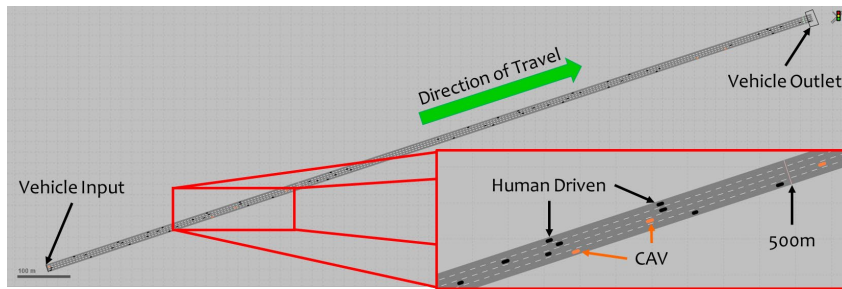
# Accomplishments

## Lane Change Microsimulation

### Non-Linear Program (NLP) Lane Change Algorithm Implementation in VISSIM

#### Simulation Scenarios

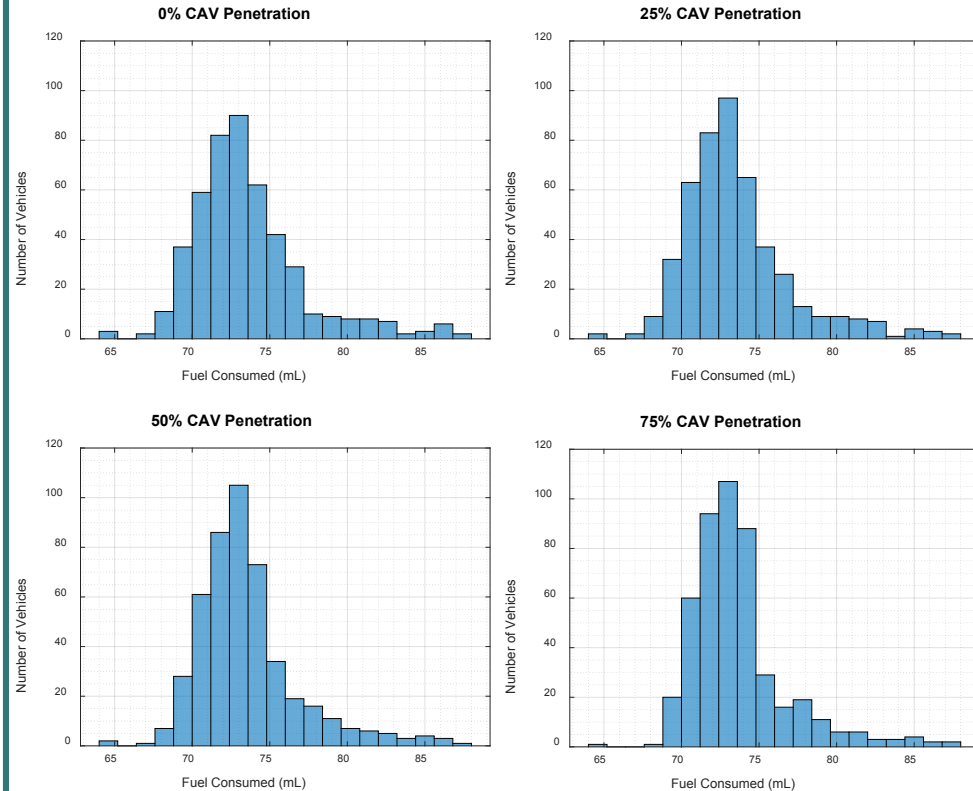
- 1300m straight link
- Volumes: 1000
- CAV penetration: 0%, 1%, 5%, 10%, 25%, 50%, and 75%
- Desired velocities distributed about 80km/h
- 30 minutes of simulation time



#### Illustrative Video



#### Analysis



CAV Penetration (%)	Mean Fuel Consumed (mL)	Variance (mL <sup>2</sup> )
0	73.58	13.24
25	73.57	11.93
50	73.56	10.93
75	73.64	9.79

# Accomplishments

## Vehicle Automation



① **LIDAR and camera Perception**



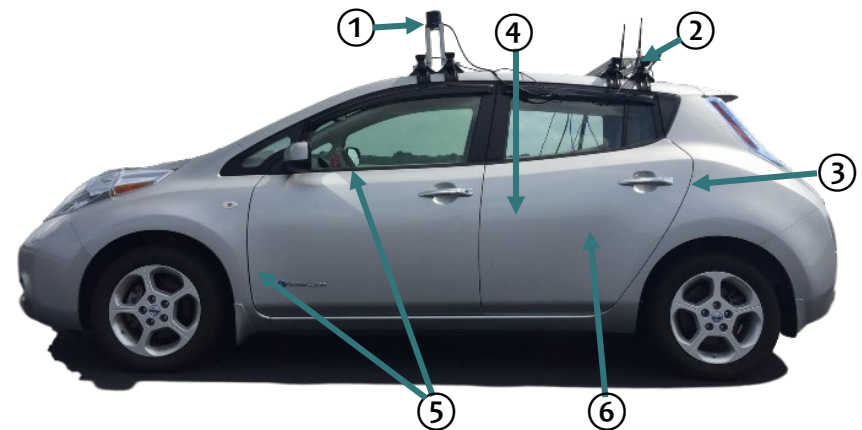
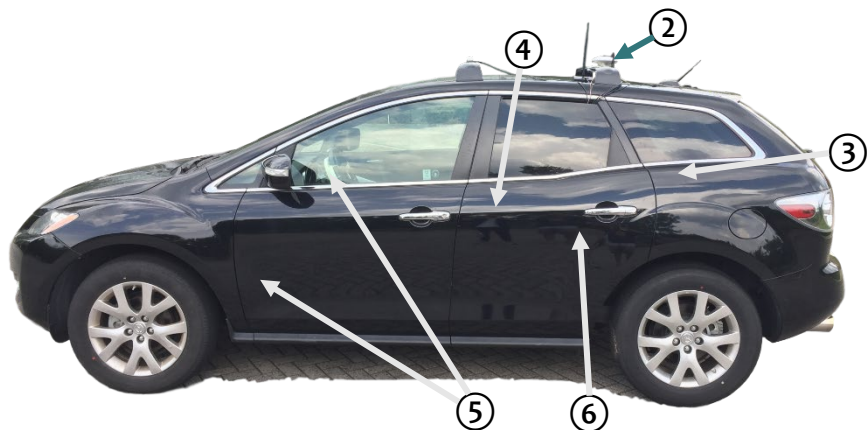
② **RTK-GPS Localization**



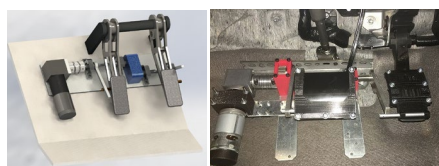
③ **IMU Attitude & heading feedback**



④ **Cellular /WiFi/DSRC Communications**

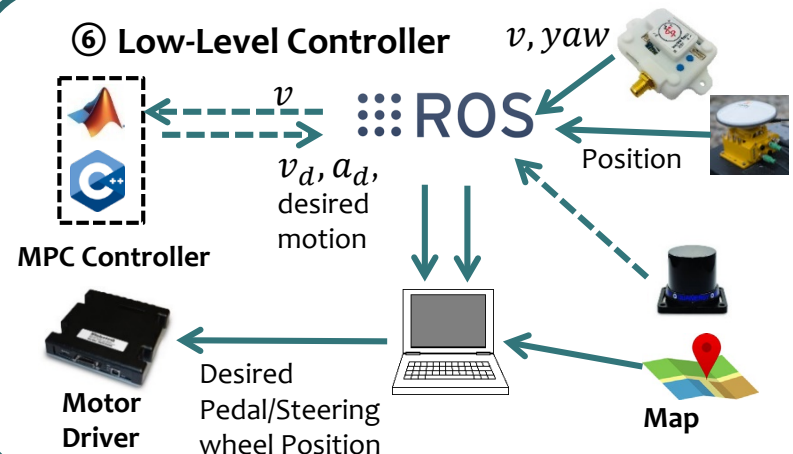


Autonomous steering robot



Autonomous acceleration and brake robot

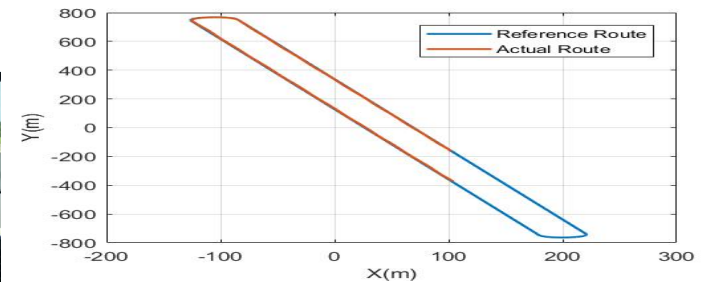
⑤ **Robotic AutoDrive System**  
Automated throttle/brake pedals and steering wheel control robots



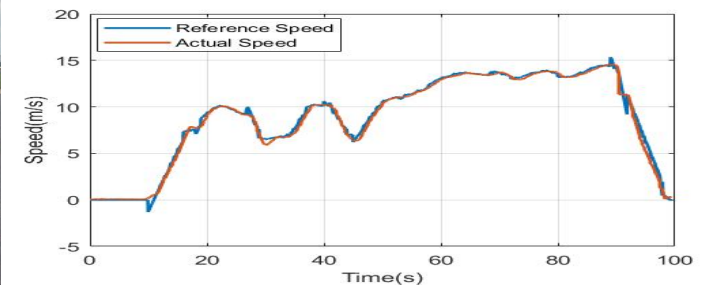
# Accomplishments

## Vehicle Automation

### Automated Vehicle Test on Test-Track



Trajectory following performance



Speed following performance

### Automated Virtual Car Following Performance

Errors of steady speed following

Nissan Leaf on Dyno	Nissan Leaf on ITIC	Mazda CX-7 on Dyno
$\pm 0.05m/s$	$\pm 0.1m/s$	$\pm 0.05m/s$

Errors of Dynamic speed following

Nissan Leaf on Dyno w. MPC	Nissan Leaf on Dyno w. IDM
0.038m/s	0.045m/s

# Accomplishments

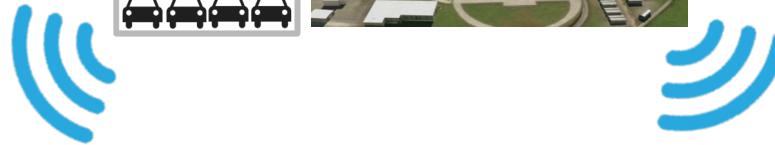
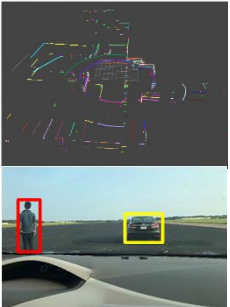
## Vehicle Automation

### Multi-CAV Test on Test-Track (In Progress)

VISSIM traffic simulation



Lidar and vision for test safety



Virtual CAV



Virtual CAV



Electric CAV

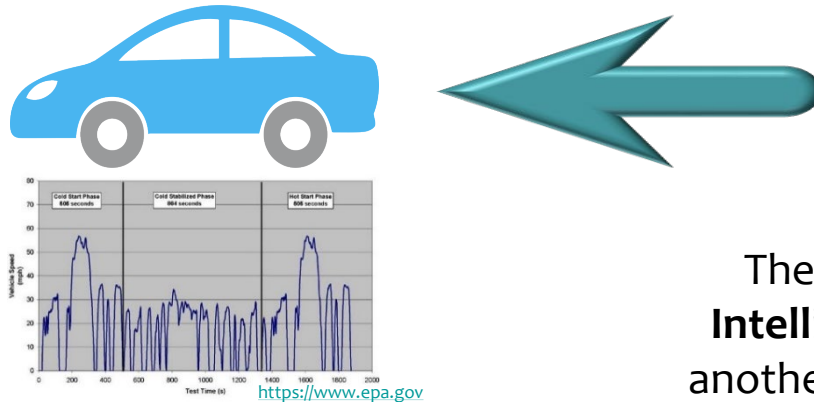


Gasoline CAV

# Accomplishments

## Preliminary Vehicle-in-the-loop Results

A single vehicle is simulated (in C++) that tracks the **FTP-75** test cycle



The real vehicle on the dynamometer follows a simulated vehicle (with no connectivity).



The real vehicle is controlled one time using **Intelligent Driver Model** (as the reference) and another time using the **MPC car following model**.

Fuel consumption reduction potential of MPC car following model compared with the Intelligent Driver Model are given below in **green color**.

### Flow Meter measurement Results

	Duration	IDM	MPC
FTP75	31min	1.82 liter	1.7 liter (+6.6%)

### Basic OBD-based Estimation Results

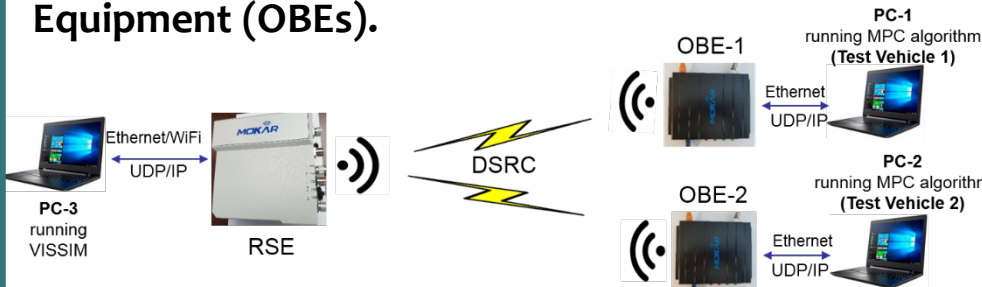
	Duration	IDM	MPC
FTP75	31min	1.66 liter	1.56 liter (+6.0%)

More energy usage improvement is expected by adding the vehicle-to-vehicle connectivity between the real and simulated vehicles.

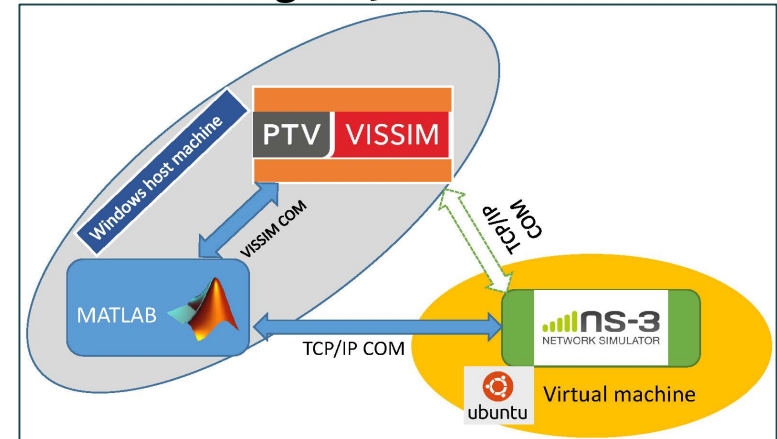
# Accomplishments

## DSRC Devices Setup + Latency Performance of Integrated simulator

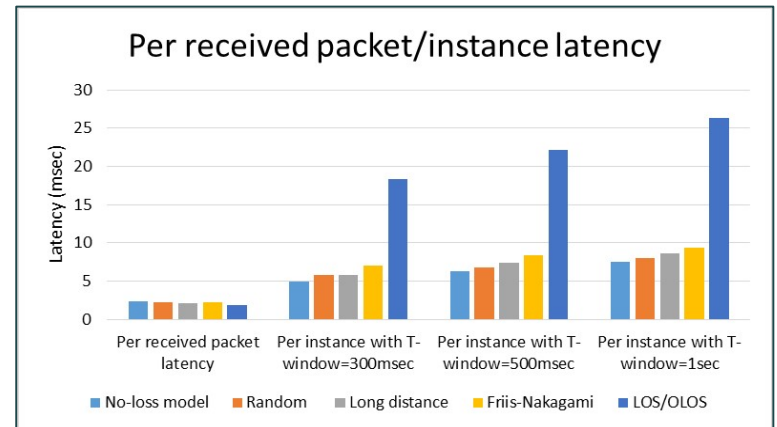
DSRC devices are set up in a lab environment including 1 Road Side Equipment (RSE) and 2 Onboard Equipment (OBEs).



We have simulated the communication network using NS-3.



NS-3 Parameter	Value
Number of vehicles	60
Safety msg size	200 bytes
Transmission rate	10 Hz
Carrier Frequency	5.9 GHz
Channel Bandwidth	10 MHz
Channel access	802.11p OCB
Data rate	6 Mbps
TXP	23 dBm
Mobility model	Waypoint Mobility (VISSIM vehicle position in every simulation sec)
VISSIM update rate	100 msec



**Per received packet latency :** is the average duration of receiving a packet from the moment it is generated.

**Per received instance latency:** is the average duration of receiving the first successful packet for specific Tx-Rx pair within T-window time.

# Responses to Reviewers' Comments

**Reviewer 6:** “The reviewer remarked that the simulation of predictive and anticipative algorithms is an important step forward for CAV analysis. The approach has initially omitted position uncertainties/error of CAVs (perfect knowledge) and assumed no communication latencies. **The reviewer noted that the positional uncertainties and data latency have the potential to change the simulation results.**”

**Response:** Later revisions of the drive cycle-based car-following simulations included random communication loss, with little effect on results after the losses were heuristically corrected [1]. The **mixed traffic simulations** are also subject to uncertainty in prediction and/or perception error. This is accounted for using chance constraint techniques [2]. **Furthermore, real communication latency, sensing error, modeling error, and prediction errors are present in the project's experimental with our test vehicles.** In addition, we have simulated the communication network using NS-3 [3]. A number of propagation loss models have been used **to realize the communication loss among simulated vehicles.**

**Reviewer 7:** “The reviewer stated that the completed work might be technically valid, but it is not clear how it is relevant. **Simulation using a test cycle like the US06 (high speed, high acceleration drive cycle) is very rigid and does not capture relevant and important variations and complexity that occur under actual driving conditions.** The reviewer said that it is probably an important step for building knowledge, but that is the limit. Improvements in efficiency do not mean much in this context until the underlying principles and behavior can be connected to larger systems or the purpose of the output is more narrowly bounded.”

**Response:** The MATLAB and VISSIM-based microsimulation environments have advanced beyond the use of imposed lead-vehicle speed profiles including the US06. As in the real world, traffic disturbances now result from road geometry, network demand, and lane position goals of individual vehicles. **In the particular case of the Arterial scenario, lane changing MPC and trip-level optimal control resulted in 16.2% reduction in energy use compared to IDM and rule-based lane change (travel time held constant), which was close to the US06 improvement of 16.7%. We also tested our vehicle using an urban drive cycle (FTP75) presented in slide 20.**

1. R. A. Dollar and A. Vahidi, “Efficient and collision-free anticipative cruise control in randomly mixed strings,” IEEE Trans. Intell. Vehicles, vol. 3, no. 4, pp. 439–452, 2018.
2. R. A. Dollar and A. Vahidi, “Automated vehicles in hazardous merging traffic: a chance-constrained approach.” To appear, 2019 9<sup>th</sup> Int. Symp. Advances in Automotive Control, IFAC, 2019.
3. “NS-3.” [Online] <https://www.nsnam.org/>.

# Collaboration and Coordination



## Clemson University

	<b>Task 1</b> (algorithms)	<b>Task 2</b> (microsimulation)	<b>Task 3</b> (experimental CAV)
PI and Co-PIs	Ardalan Vahidi, Beshah Ayalew	Ardalan Vahidi, Beshah Ayalew, D. Karbowski	Yunyi Jia, Ardalan Vahidi
Post-doctorals	Ali Reza Fayazi, G. G. Md. Nawaz Ali		
Grad. Students	R. Austin Dollar, Tyler Ard, Longxiang Guo, Nathan Goulet, Andinet Hunde		



## Argonne National Laboratory

Co-PI: Mr. Dominik Karbowski

To estimate energy efficiency using ANL's detailed powertrain simulation tool Autonomie.



## International Transportation Innovation Center

Sub-contractor: Dr. Joachim G. Taiber

Responsible for the physical implementation of the communication network at the testbed, and to provide physical testbed access to perform the experiments.



## PTV Group

Provides the VISSIM traffic microsimulation tool, technical support, and traffic data.

# Remaining Challenges and Barriers

## Algorithms



- Accurate prediction of surrounding vehicles' motion remains a challenge.

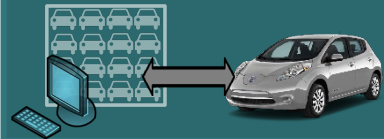
## Microsimulations

PTV

VISSIM

- High variance in Vissim simulations requires large number of simulations.
- How to generate relevant scenarios and how to measure performance meaningfully. Results are sensitive to post-processing.
- Vissim requires very precisely tuned parameters to realistically model human driving behavior.

## VIL Simulations



Most issues have been resolved. The only remaining issue is:

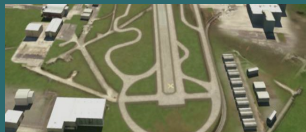
- Computation + communication delay may pose a challenge in some scenarios.

## CAV Instrumentation



- Improve speed control accuracy in low speed range (below 1.4m/s).
- Reduce trajectory tracking error at high speed.

## Test Track



- Compatibility issues for sending/receiving custom data between products from different manufacturers (Cohda and iSmartWays devices).
- The closed track is available for testing for limited days only.

# Proposed Future Research

## Upcoming Milestones:

- Detailed Energy Consumption Evaluation in Autonomie.
- Multi-Lane microsimulations & experiments.
- Collaborative Guidance.

## Future work for the rest of FY19:

- Estimating the energy efficiency impact via high fidelity models in collaboration with Argonne National Lab and their detailed powertrain simulation tool Autonomie.
- Completing a test track setup for DSRC communication between experimental and simulated vehicles.
- Demonstrating the energy savings via our vehicle-in-the-loop experimental testbed that includes two experimental CAVs driven on a test track.
- Running multi-lane co-simulations and measure energy use of test vehicle when collaborating with simulated vehicles.
- Designing new collaborative guidance algorithms for CAVs aimed at reducing energy use of equipped vehicles.

## Overall Objective

**Propose anticipative and collaborative guidance schemes for CAVs**, to achieve at least 10% gain in energy efficiency across a mixed traffic fleet with 30% penetration of CAVs.

## Our Approach

- **Formulate a vehicle guidance scheme** that allows the CAVs to plan their energy optimal and safe future motion plan using the information obtained from our **Traffic Perception and Prediction algorithms**.
- To verify the energy efficiency benefit of the proposed vehicle guidance scheme, we use customized **traffic microsimulations**.
- To verify the energy efficiency benefit of the proposed vehicle guidance scheme in a near real-world condition, we use **test vehicles in a novel vehicle-in-the-loop co-simulation environment**.

## Key Technical Accomplishments

- Multi-agent microsimulations in MATLAB show anticipative vehicle guidance contributes 9% to 16% reduction in homogeneous fleet energy use. Efficiency also steadily improved in partially-connected scenarios.
- Integrated the proposed car-following & lane selection schemes into Vissim.
- Preliminary Vissim microsimulations showed fuel benefits across all penetrations and volumes.
- Completed robotic autonomous driving system implemented in a Nissan Leaf & Mazda CX7.
- Preliminary experiments showed about 6% fuel consumption reduction by our anticipative car-following algorithm in absence of communication.
- Characterized the communication delay and packet drops using VISSIM.

# Technical Back-Up Slides

### Lane Changing MPC with MIQP Objective

$$J = x_e^T(N) P x_e(N) + \sum_{i=0}^{N-1} [x_e^T(i) Q x_e(i) + u_e^T(i) R u_e(i)]$$

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & q_l & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad P = \begin{bmatrix} q_s & 0 & 0 & 0 & 0 \\ 0 & q_v & 0 & 0 & 0 \\ 0 & 0 & q_a & 0 & 0 \\ 0 & 0 & 0 & q_l & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$R = \begin{bmatrix} q_a & 0 \\ 0 & q_l \end{bmatrix}$$

### Chance Constraints for Collision Avoidance

$$-s - M(2 - \mu_{\lambda a} - \mu_{\lambda b}) - M\beta_{\zeta}^C \leq -ES_{min}^{\zeta} - d_r + \epsilon_1$$

$$s - M(2 - \mu_{\lambda a} - \mu_{\lambda b}) - M\beta_{\zeta} \leq ES_{max}^{\zeta} - d_r + \epsilon_1$$

$$\beta_{\zeta}, \mu_{\lambda a}, \mu_{\lambda b} \in \{0, 1\}$$

$$d_r = F_s^{-1}(\alpha) - ES$$

### Trip-Level Optimal Control

$$\min J = \int_{t_0}^{t_f} \dot{v}^2 dt$$

$$\text{s.t. } s(t_0) = s_0, \quad s(t_f) = s_f$$

$$v(t_0) = v_0, \quad v(t_f) = 0$$

$$\dot{s} = v$$

$$v \leq \bar{v}$$

#### Case I

$$a^*(t) = \frac{1}{2}c_1 t - c_2 \quad \forall t$$

#### Case II

$$a^*(t) = \begin{cases} -\frac{1}{2}\lambda_2 = \frac{1}{2}c_1 t - c_2^I & ; \quad t < t_1 \\ 0 & ; \quad t_1 \leq t < t_2 \\ -\frac{1}{2}\lambda_2 = \frac{1}{2}c_1 t - c_2^{\text{III}} & ; \quad t_2 \leq t < t_f \end{cases}$$

#### Case III

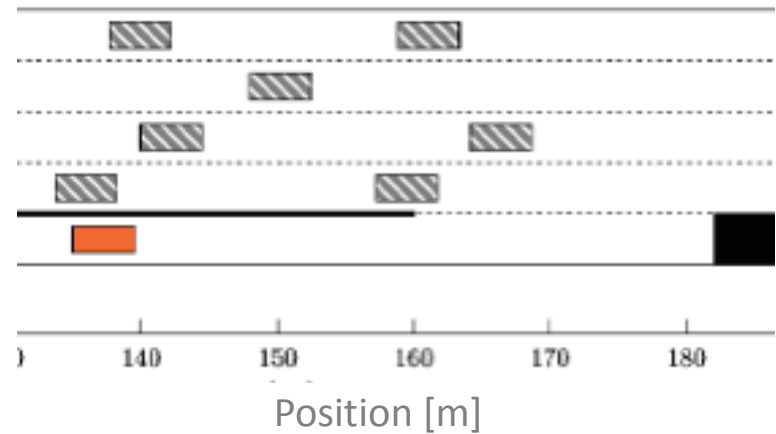
$$a^*(t) = \begin{cases} 0 & ; \quad t \leq t_1 \\ -\frac{1}{2}\lambda_2 = \frac{1}{2}c_1 t - c_2 & ; \quad t_1 \leq t < t_f \end{cases}$$

# Technical Back-Up Slides

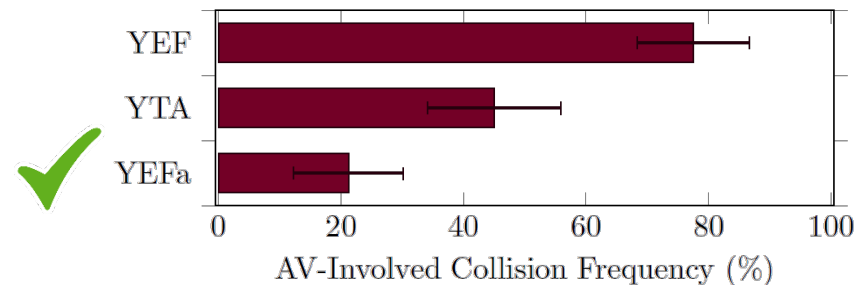
## Chance Constraint Design



The environment of a real AV collision was modeled in MATLAB.



Designs were compared and the safest was selected.



### Lane Changing MPC with NLP Objective

$$\min_{\mathbf{u}_k} \sum_{k=1}^N \left[ \|F_{l,k}\|_{Q_f}^2 + \|G_k\|_{Q_g}^2 \right] + \sum_{k=1}^{N-1} \left[ \|H_k\|_{Q_h}^2 + \|u_k\|_R^2 \right]$$

Subject to:  $\dot{x} = f(x, u), x \in X, u \in U$   
 $c(x, u) \geq 0$

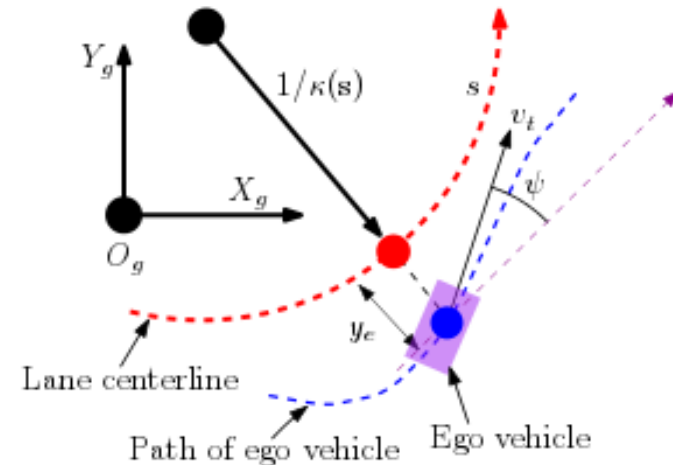
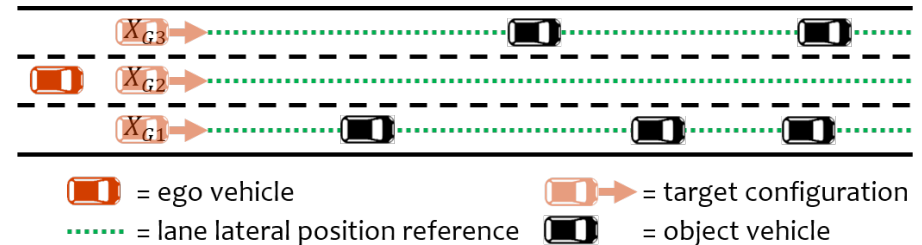
Where:  $F$  = Lane dependent cost (a weighted blend of the costs for tracking the center and reference speed of each lane)

$G$  = Lane independent cost (e.g. desired velocity)

$H$  = Predictability cost

Further:

$$x = \begin{bmatrix} s \\ y_e \\ \psi \\ v_t \\ a_t \end{bmatrix}; \quad \dot{x} = \begin{bmatrix} v_t \left( \frac{1}{1 - y_e \kappa(s)} \right) \cos \psi \\ v_t \sin \psi \\ a_t \\ -\tau_\psi \psi \\ -\tau_a a_t \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \tau_\psi & 0 \\ 0 & \tau_a \end{bmatrix} \begin{bmatrix} \psi_d \\ a_d \end{bmatrix}$$



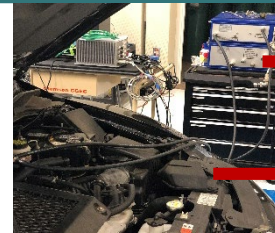
- Goulet, N. and Ayalew, B. "Coordinated Model Predictive Control on Multi-Lane Roads". In Proceedings of the ASME 2019 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC 2019). August 18-21, 2019. Anaheim, CA, USA.

# Technical Backup

## Evaluating our OBD-based fuel rate estimations<sub>(Combustion test vehicle)</sub>

- Our OBD Logger App was extended to read and collect 11-bit CAN protocol of this test vehicle.
- The maximum data sampling frequency was increased from 2Hz to 5Hz.

- In order to evaluate our OBD-based fuel rate estimations, we tracked the actual fuel in the tank and also used a flow meter to measure the actual fuel consumed by the engine.

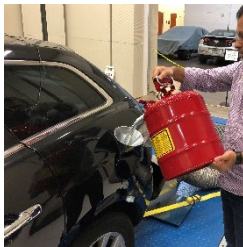


**AVL KMA Mobile Flow Meter**

**Mazda-CX7 Test Vehicle**

### Step 1

Add fuel to an empty tank.



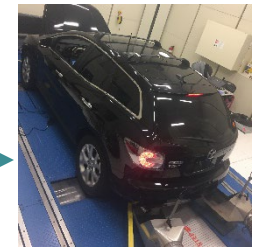
### Step 2

Log flow meter data  
& OBD data simultaneously.



### Step 3

Run on a chassis dynamometer until run out of fuel.



**We repeated the process three times putting 1 gal, 2.5 gal, and 3 gal in an empty tank.**

The errors in flow meter measurements and OBDII estimations compared with the initial fuel in the tank are given in **red color**.

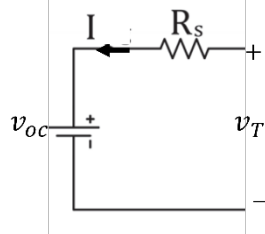
	Duration	Fuel Tank	Flow Meter	OBDII (basic method)	OBDII (calibration method)
Test 1 (1 gal)	1h 20min	3.79 liter	3.94 liter (+4.0%)	3.63 liter (-4.1%)	In progress
Test 2 (2.5 gal)	3h 41min	9.46 liter	10.22 liter (+8.0%)	8.59 liter (-9.3%)	In progress
Test 3 (3 gal)	1h 45min	11.36 liter	11.51 liter (+1.4%)	11.09 liter (-2.3%)	In progress

# Technical Backup

## Energy Consumption Measurements (Battery Electric test vehicle)

- Unlike our combustion test vehicle, the specification of the packets sent to the OBD port of our electric Nissan Leaf vehicle are not published by the vehicle manufacturer.
- Our OBD Logger App was extended to collect the **battery's current, voltage, state-of-charge (SOC), and capacity** via OBD port of the Nissan Leaf.

- To estimate the resistive energy loss of the battery, we estimated the battery's internal resistance value using the collected OBD data.

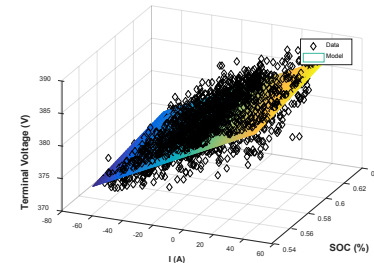


$$v_T = v_{oc} + R_s \cdot I$$

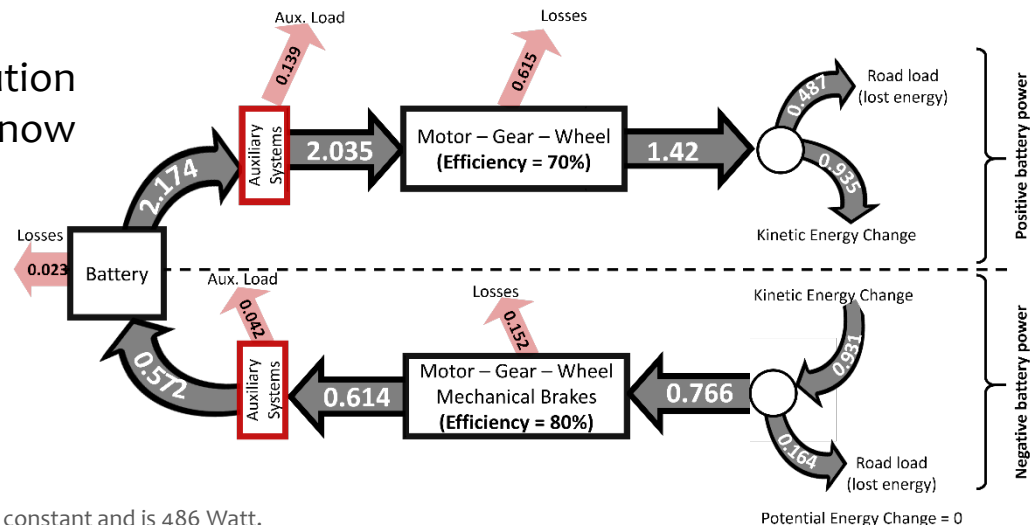
$$v_{oc} = a \cdot SOC(t) + b$$

$$v_T = a \cdot SOC(t) + R_s \cdot I + b$$

- The terminal voltage ( $v_T$ ), and charging/discharging current ( $I$ ) are available via OBD port. By linear regression\* we obtained  $R_s = 0.1 \text{ (ohm)}$ .



- The estimated energy distribution (kWh) for our electric vehicle can now be plotted for each road test\*\*:



\* Assuming Open Circuit Voltage ( $v_{oc}$ ) is a linear function of SOC:

\*\* Assuming that the power consumed by the auxiliary systems is constant and is 486 Watt.